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Hamburg, 28 September 2016

Drift in climate prediction and the need for a balanced initialisation

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SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

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What

Environmental modelling and forecasting

Why

Our strength …
… research …
… operations …
… services …
… high resolution …

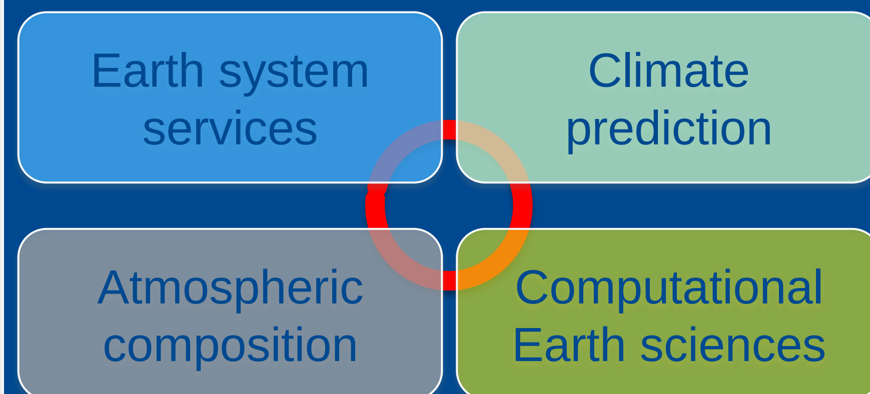
How

Develop a capability to model air quality processes from urban to global and the impacts on weather, health and ecosystems

Implement climate prediction system for subseasonal-to-decadal climate prediction

Develop user-oriented services that favour both technology transfer and adaptation

Use cutting-edge HPC and Big Data technologies for the efficiency and user-friendliness of Earth system models



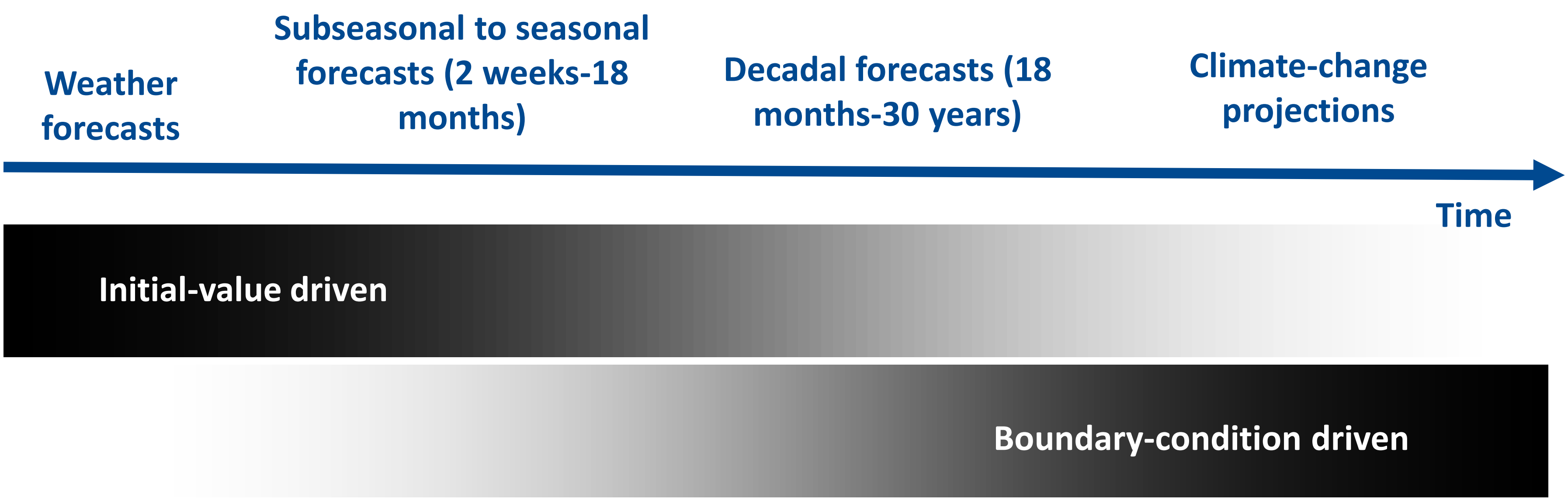
Many of the ideas in this presentation were discussed at the SPECS/PREFACE/WCRP workshop:

http://www.bsc.es/es/earth-sciences/events/specsprefacewcrp-workshop

- The objective was to show the latest results on the sources and conditions behind the initial shock and drift, to assess the impact on the forecast quality, and to organise some coordinated work taking advantage of the WCRP's Working Group on Seasonal-to-Ineranannual Prediction (WGSIP) initial shock and drift project: the Long Range Forecast Transient Intercomparison Project.
- Sensitivity to the initialisation methodology (coupled initialisation) and product (GSOP) was central.
- A discussion for recommendations for bias adjustment in CMIP6 also took place.

Climate prediction time scales

Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and validation/verification.

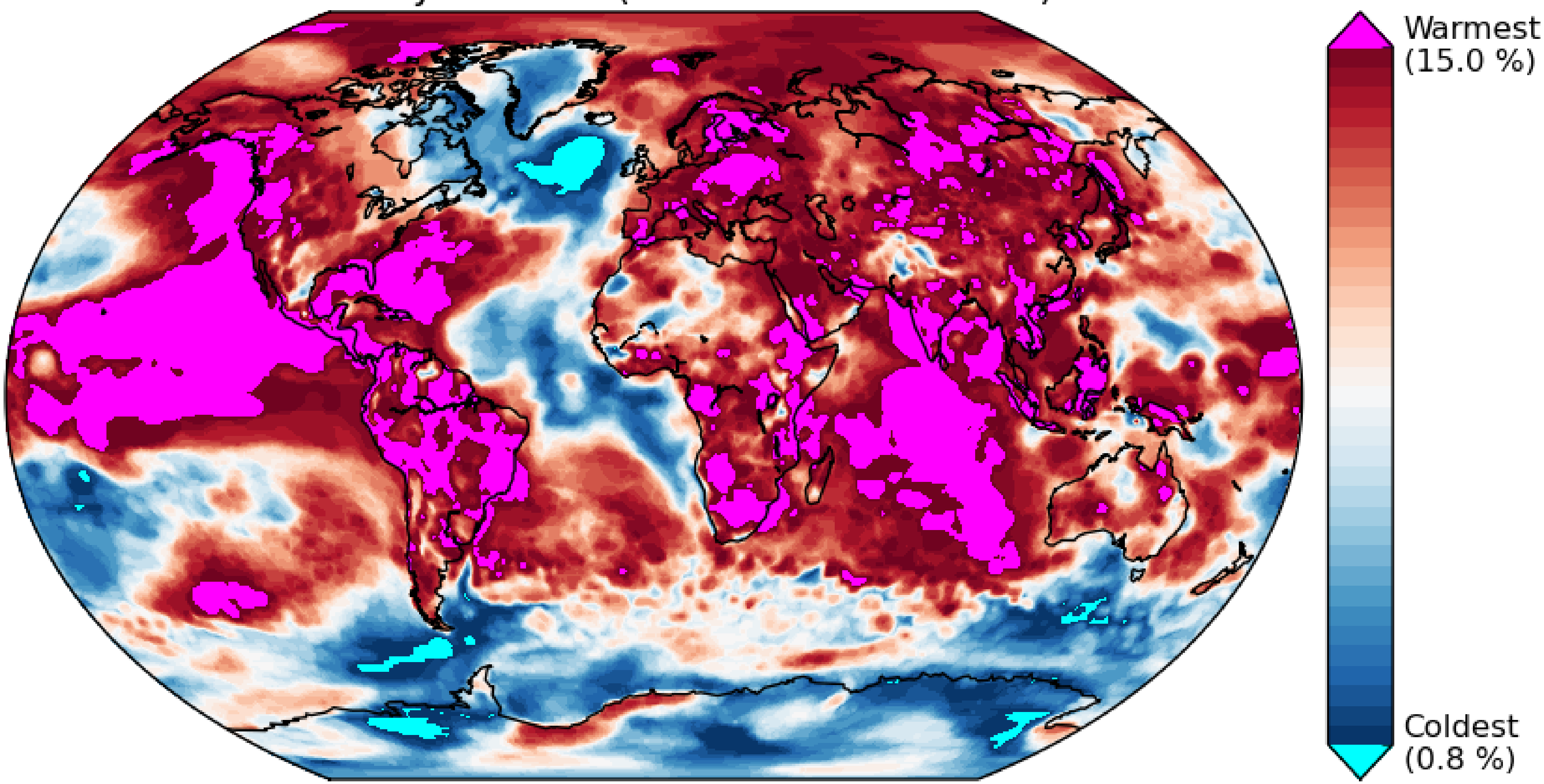


Adapted from Meehl et al. (2009)

The type of signal to be predicted

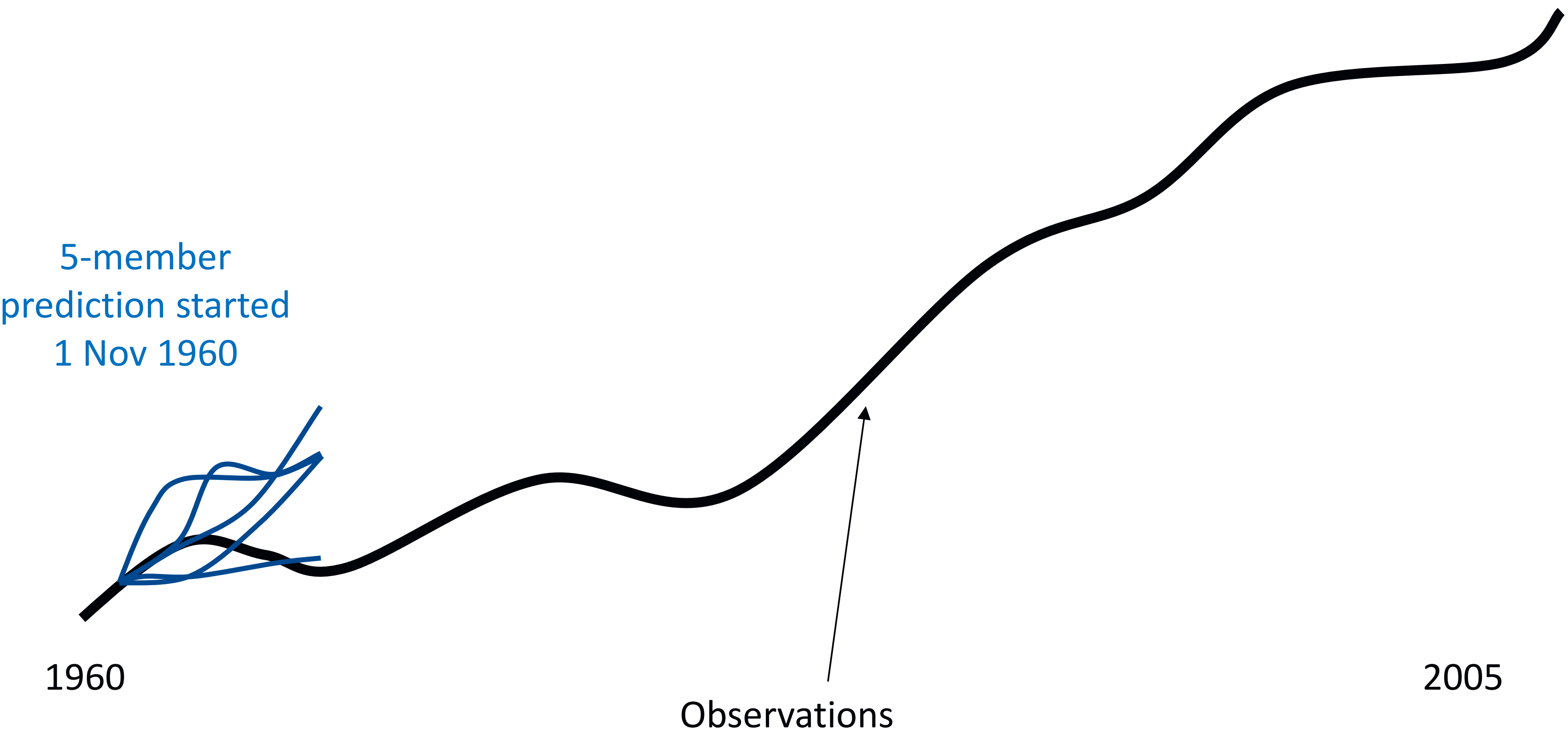
Ranking of the 2015 annual mean temperature over the last 37 years from ERA Interim.

Annual mean 2m temperature
Rank of year 2015 (reference: 1979-2015)

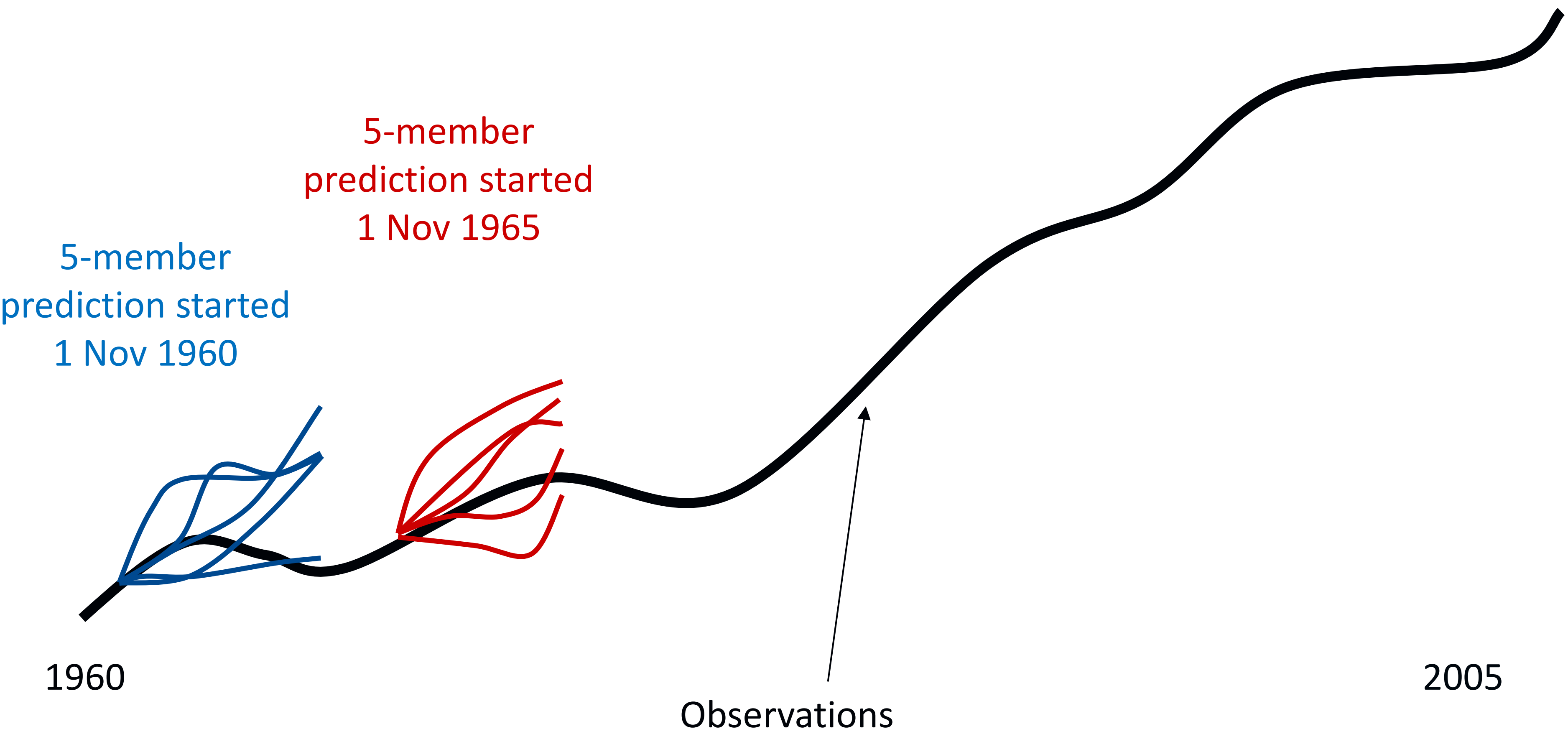


Data: ERA-Interim. Figure: F. Massonnet - BSC

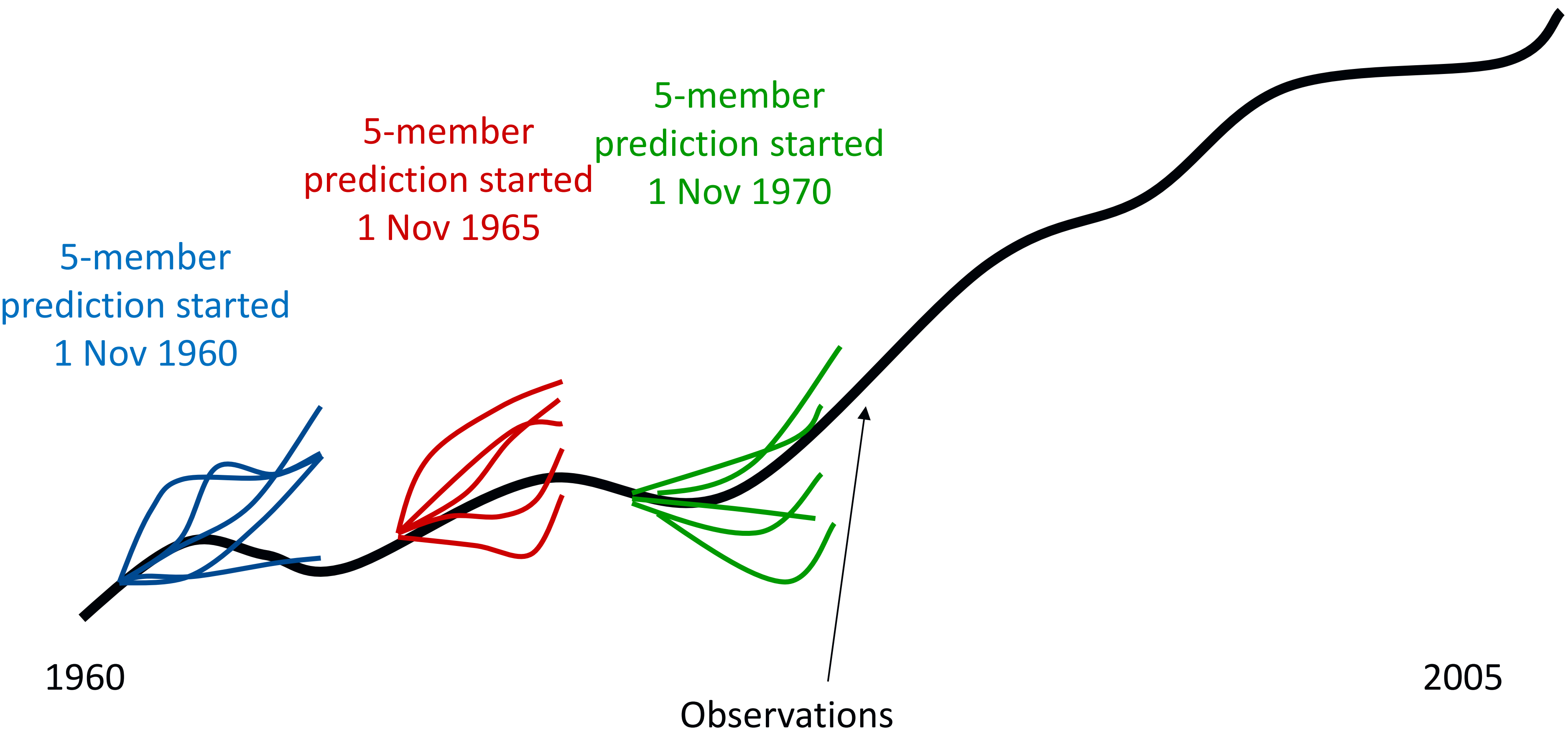
Climate predictions



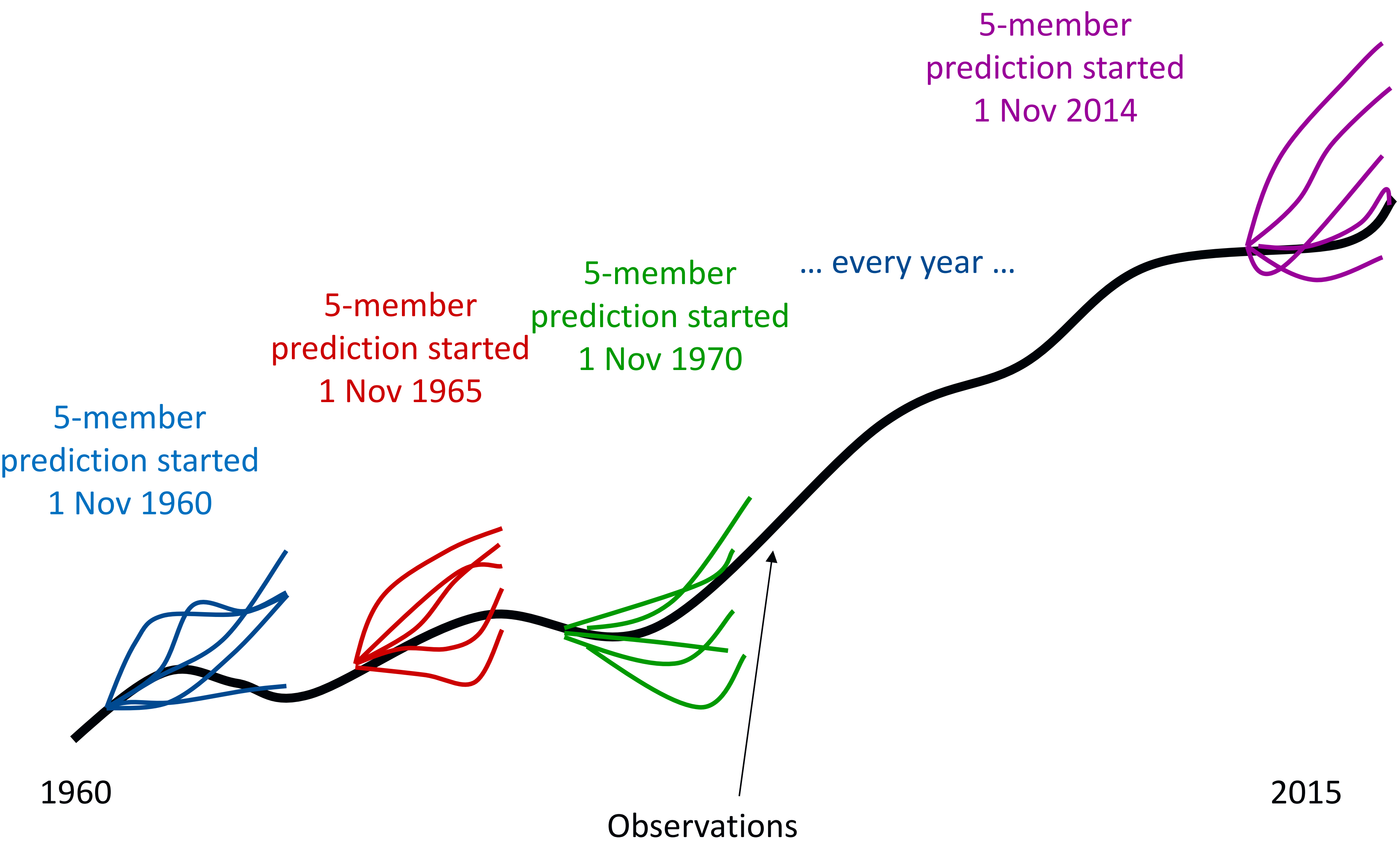
Climate predictions



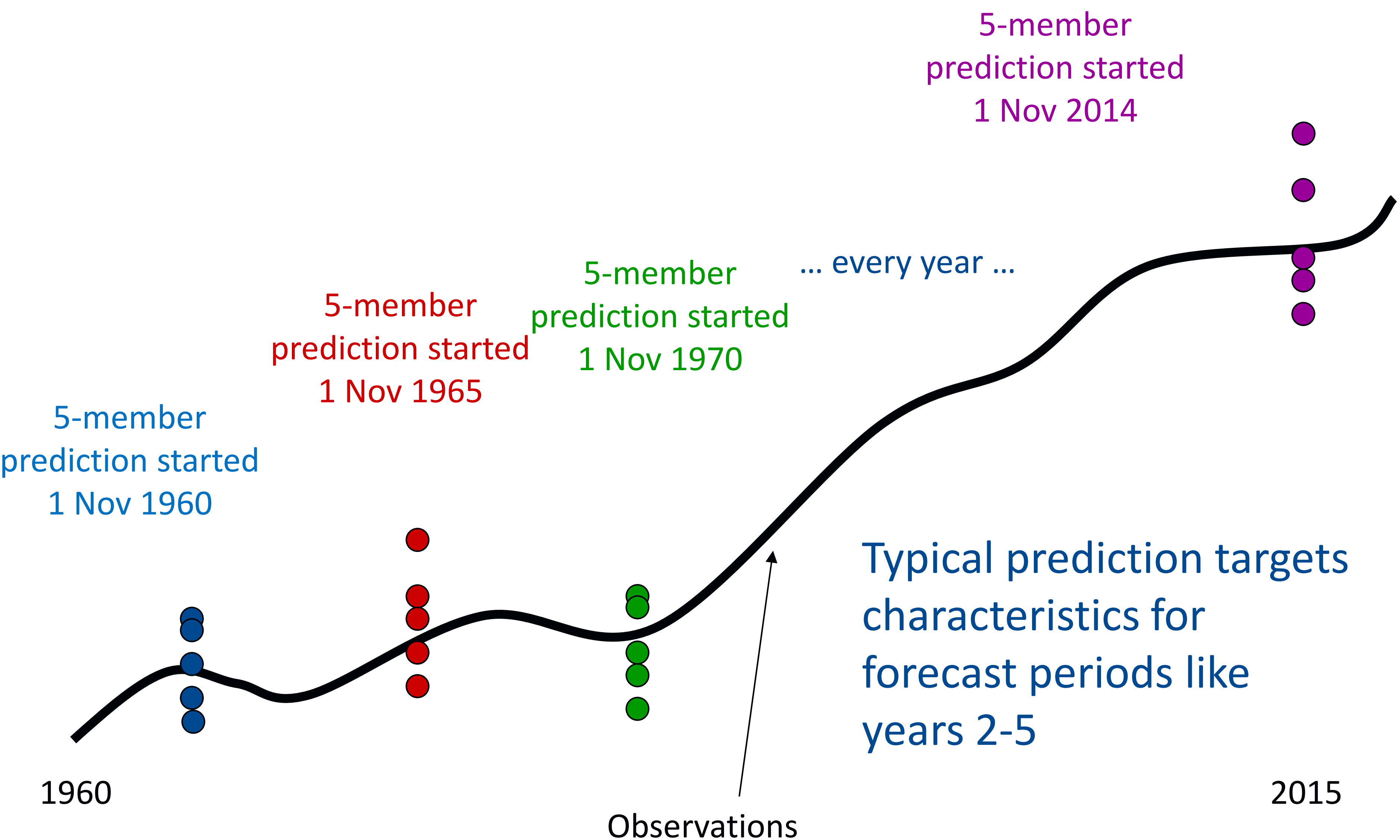
Climate predictions



Climate predictions



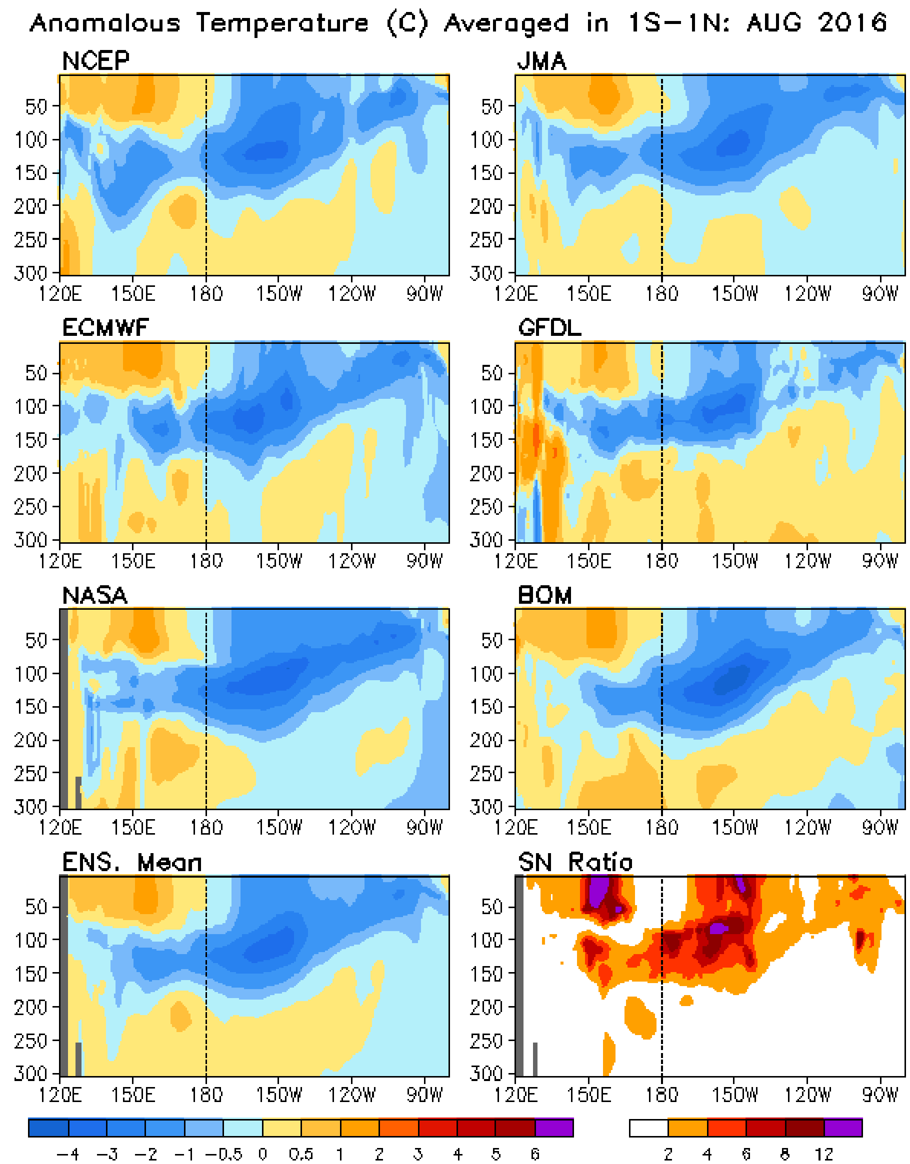
Climate predictions



Typical prediction targets characteristics for forecast periods like years 2-5

Initial condition uncertainty

- Real-time ocean analysis comparison. Temperature anomalies along the Equator based on 1981-2010 climatology.
- Large spread in real-time initial conditions (similar message from CLIVAR-GSOP).
- Good observations of the whole system are absolutely fundamental for accurate predictions.
- Initial condition uncertainty taken into account in ensemble systems.



http://www.cpc.ncep.noaa.gov/products/GODAS/multiora_body.html

The usual way to look at forecasts

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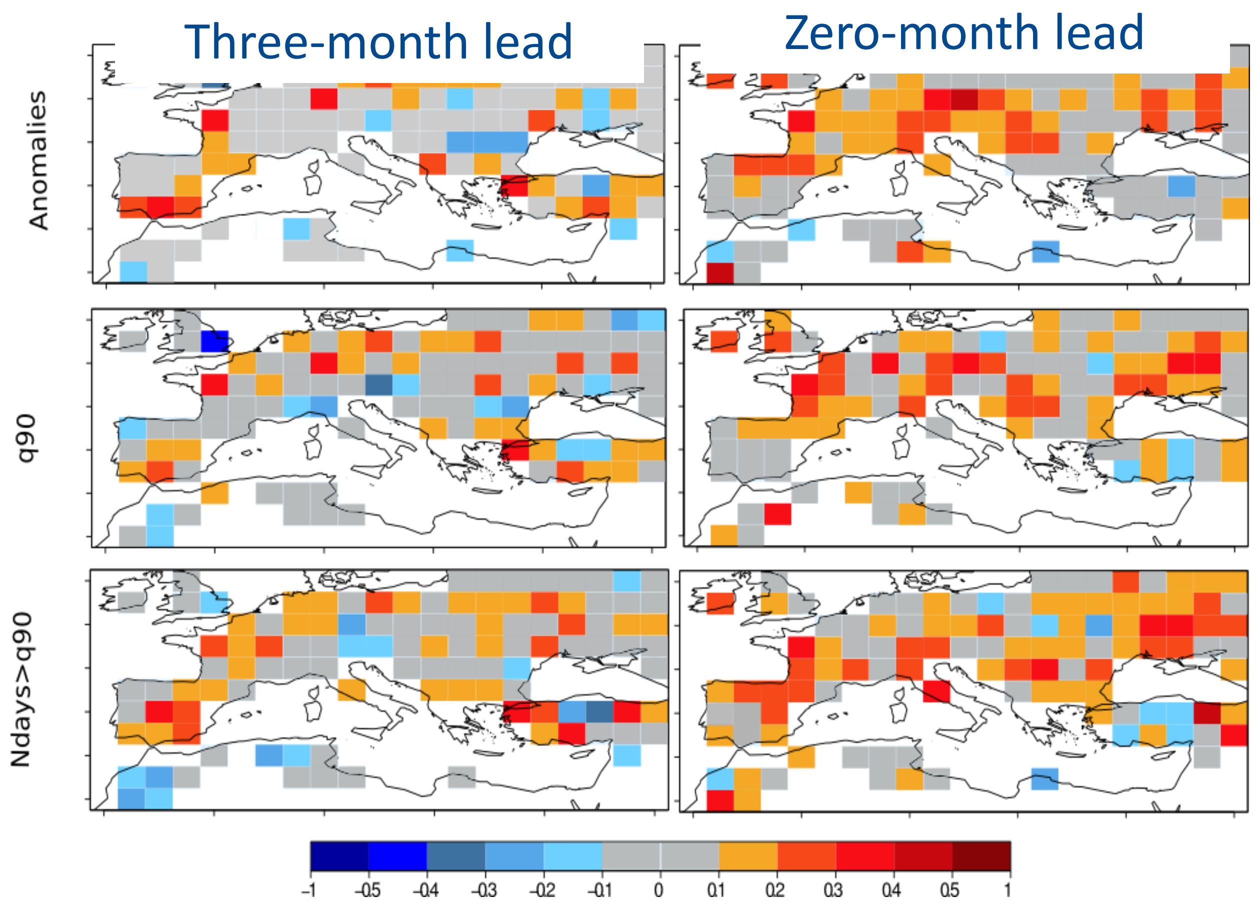
Correlation (against EObs) of ensemble-mean forecasts of (top) monthly-mean precipitation anomalies, (middle) 90th monthly percentile and (bottom) number of days with precipitation above the 90th climatological percentile for August. Hindcasts over 1960-2005 from DePreSys_PP initialized in May (left) and August (right).

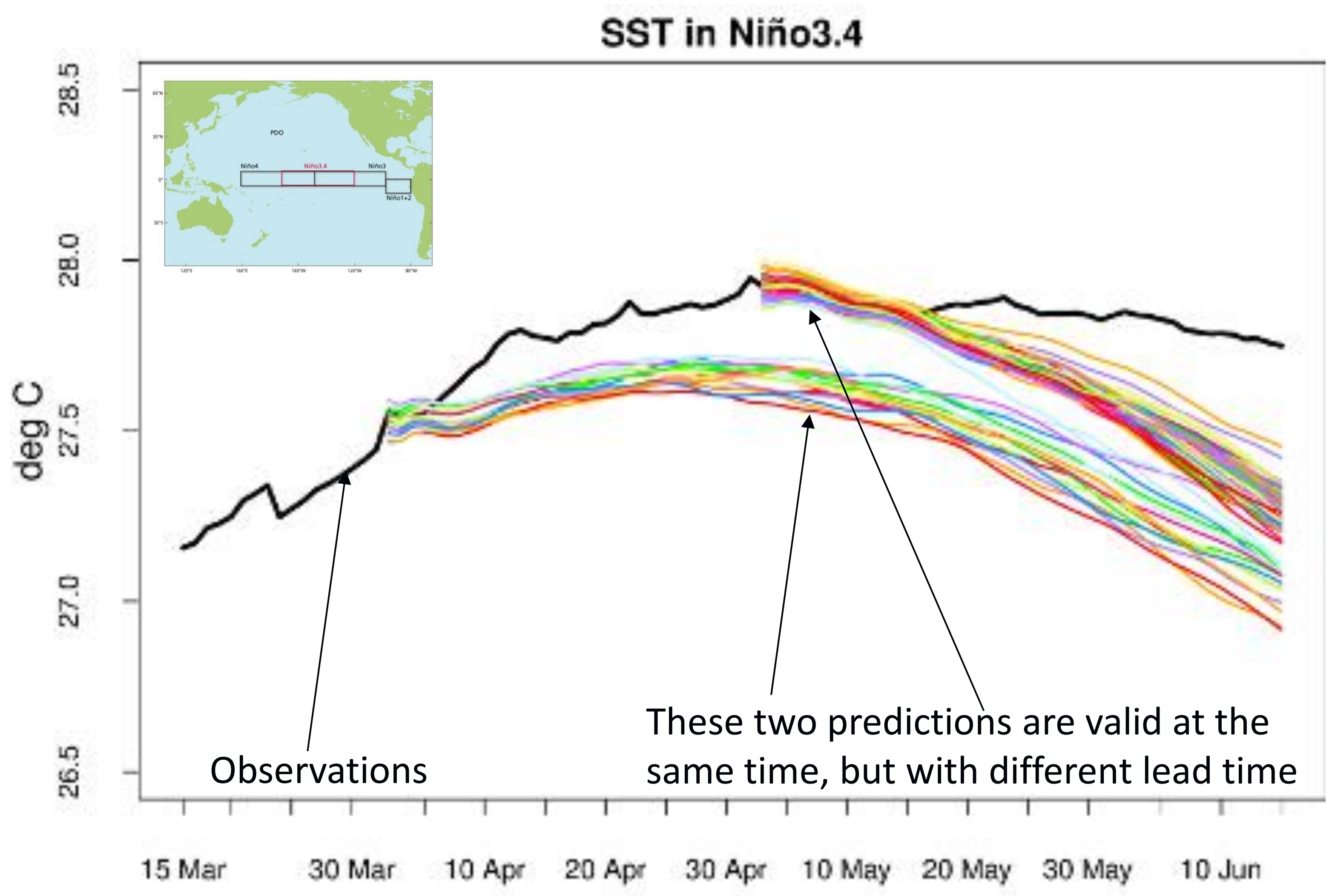
The systematic error information is usually not available, nor used.



Doblas-Reyes et al. (2013, WIRES Clim. Ch.)

A simple illustration of drift

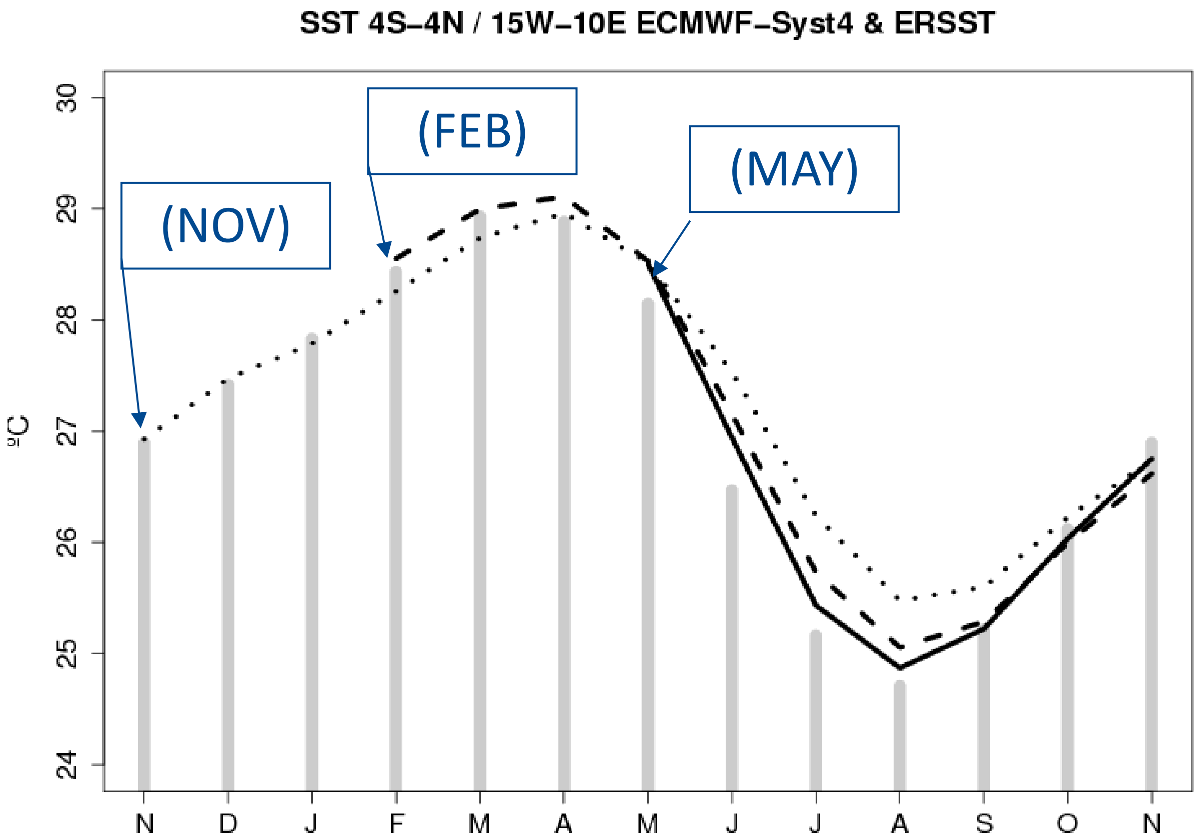
SST predictions over the Niño3.4 region from ECMWF System 4 starting on the 1st of April and May of a particular year.



Drift in the tropical Atlantic

Tropical Atlantic (4ºS-4ºN, 15ºW-10ºE) averaged SST 1982-2008 for ERSST (observations, grey bars) and ECMWF System 4 with start dates May, February (3-months ahead), and November (6 months).

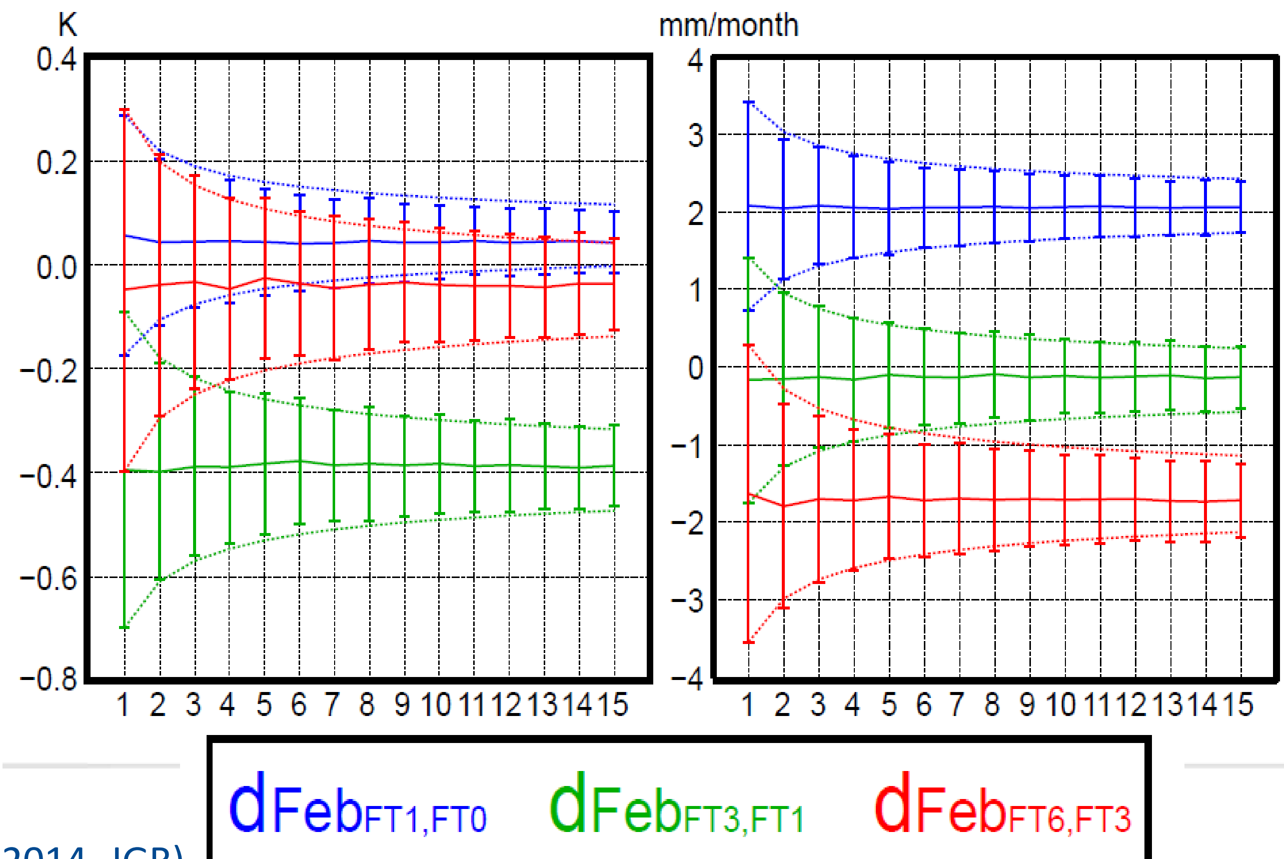
The drift is the set of physical processes the model uses to shift from the initial conditions to its attractor.



Doblas-Reyes et al. (2013, WIRES Clim. Ch.)

Drift is non-monotonic

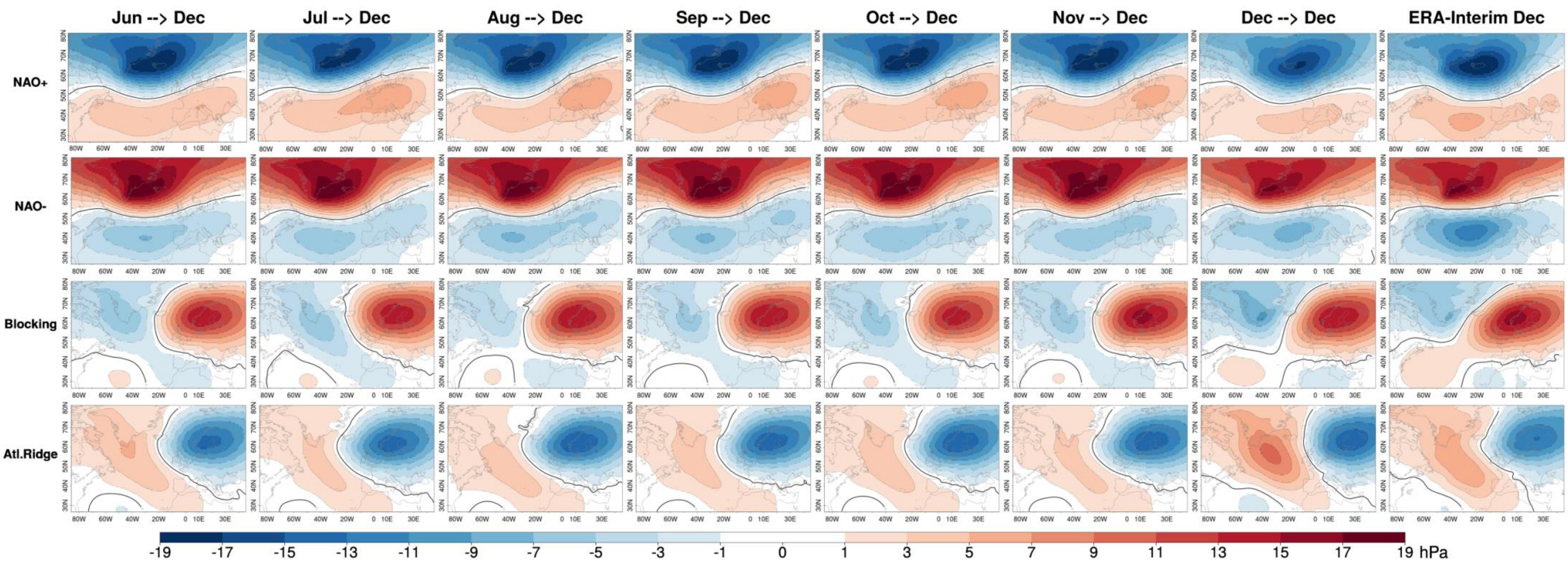
Drift for the ECMWF System 4 forecasts for European temperature (left) and precipitation (right) in February as a function of the ensemble size with different start dates. Each colour for a different lead time: second minus first forecast month (J-F), fourth minus second month (N-J) and seventh minus fourth month (A-N).



Manzanas et al. (2014, JGR)

Drift estimates: variability

North Atlantic weather regimes (based on sea level pressure) for December for ERAInterim (right) and the ECMWF System 4 hindcasts over 1981-2014 with decreasing lead time from left to right (from six to zero months).



Cortesi et al. (2016, BSC Tech Memo)

More examples: decadal predictions

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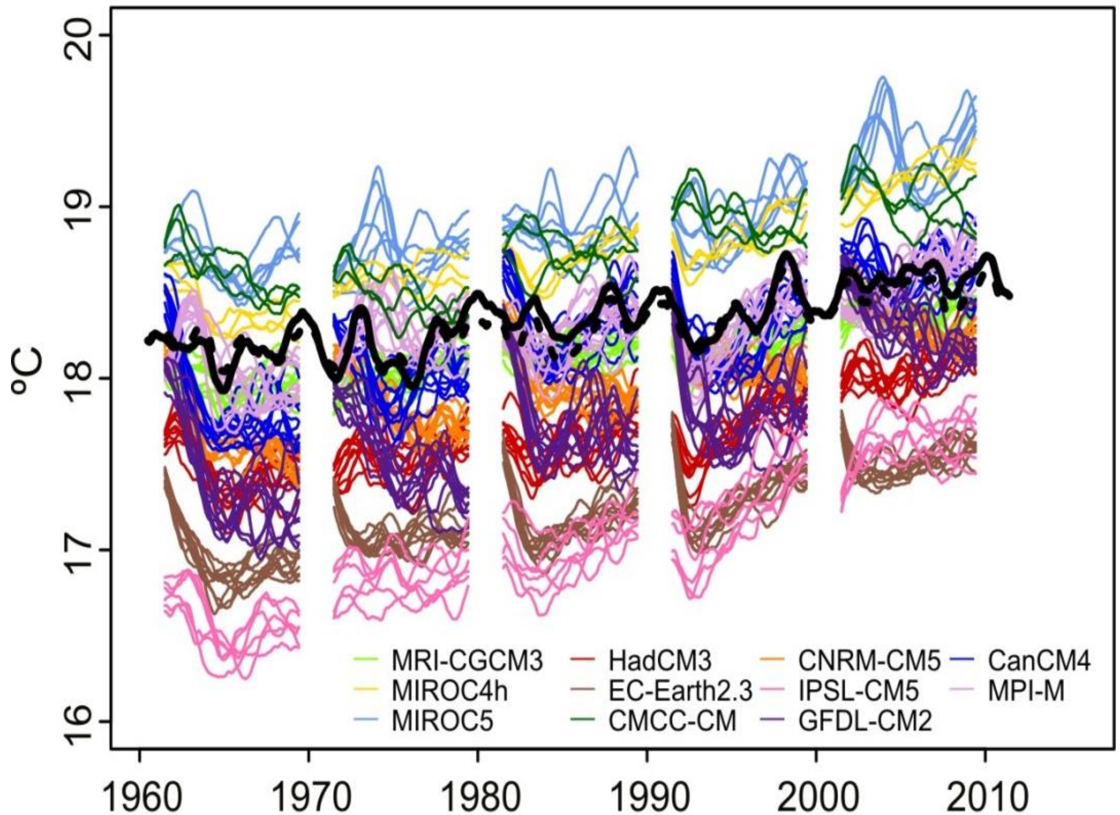
Global mean near-surface air temperature over the ocean (one-year running mean applied) from CMIP5 hindcasts. Each system is shown with a different colour. NCEP and ERA40/Int used as reference.

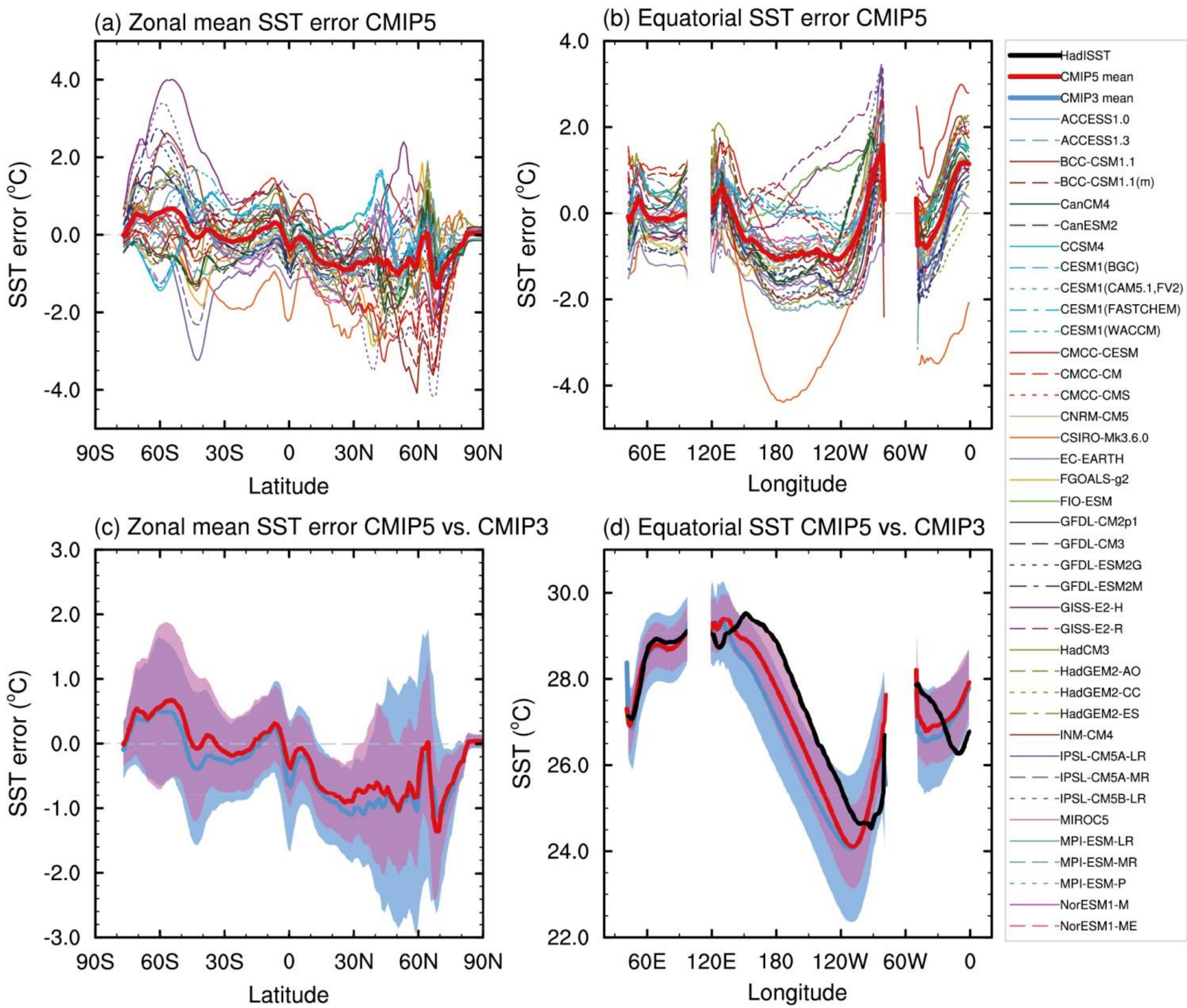
Shock and drift is the norm



IPCC AR5 WGI (2013)

Drift sources: model systematic error

CMIP5 model systematic error improved over CMIP3, but …

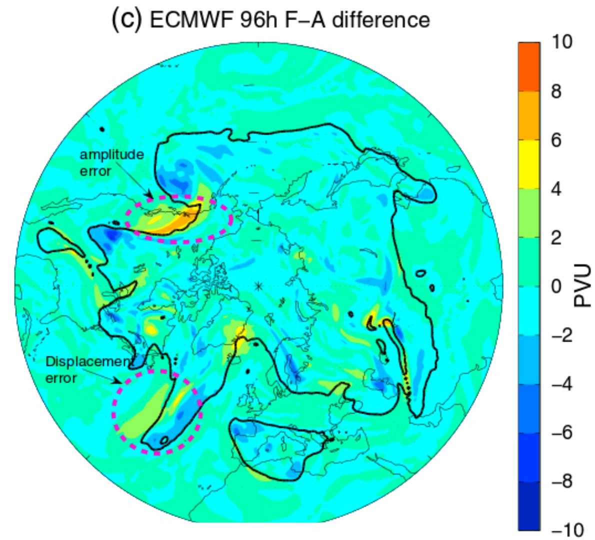


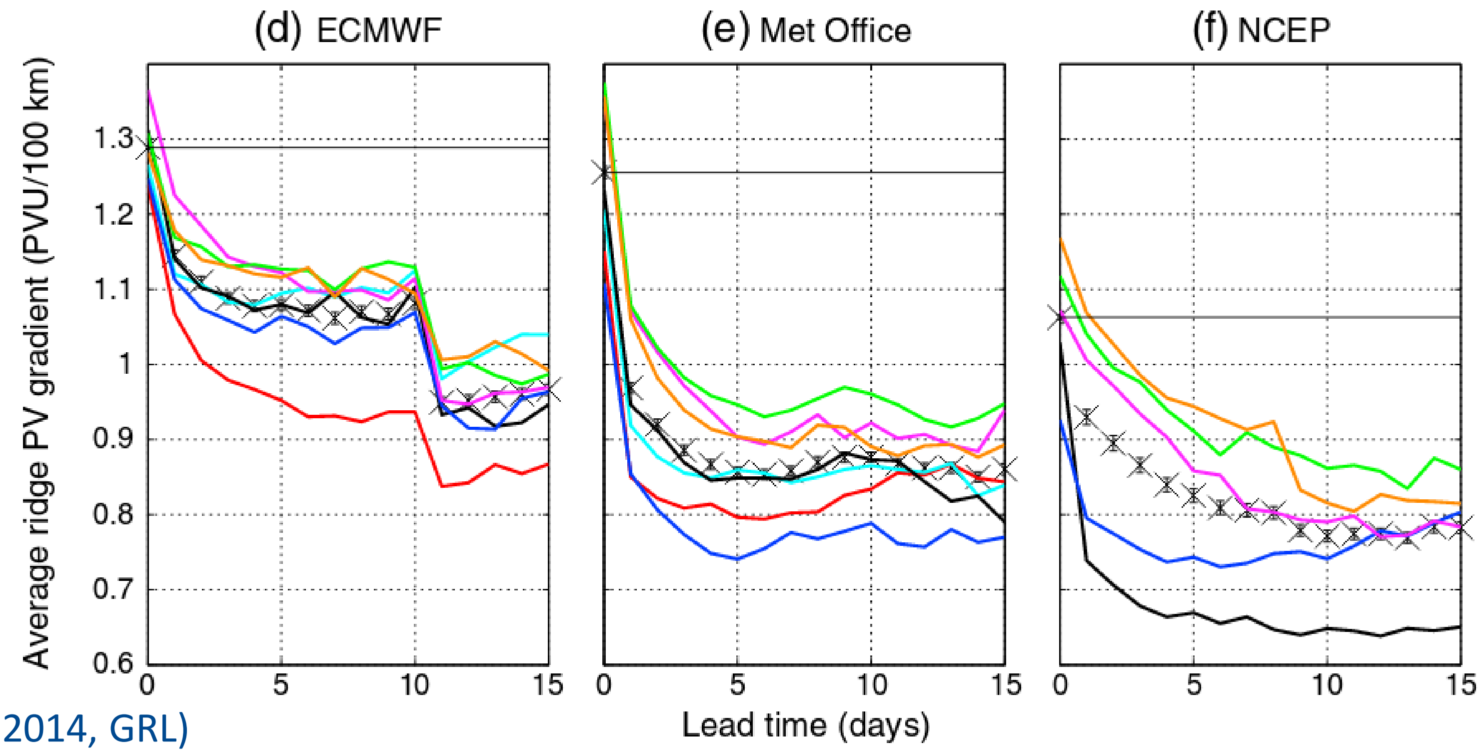
IPCC AR5 WGI (2013)

Drift sources: fast processes

Isentropic PV gradient (320 K) averaged over the flanking ridges from 2006 to 2011 (one colour per year) compared to the analysis mean value (horizontal grey).

The atmosphere smooths out gradients very quickly during the forecast.





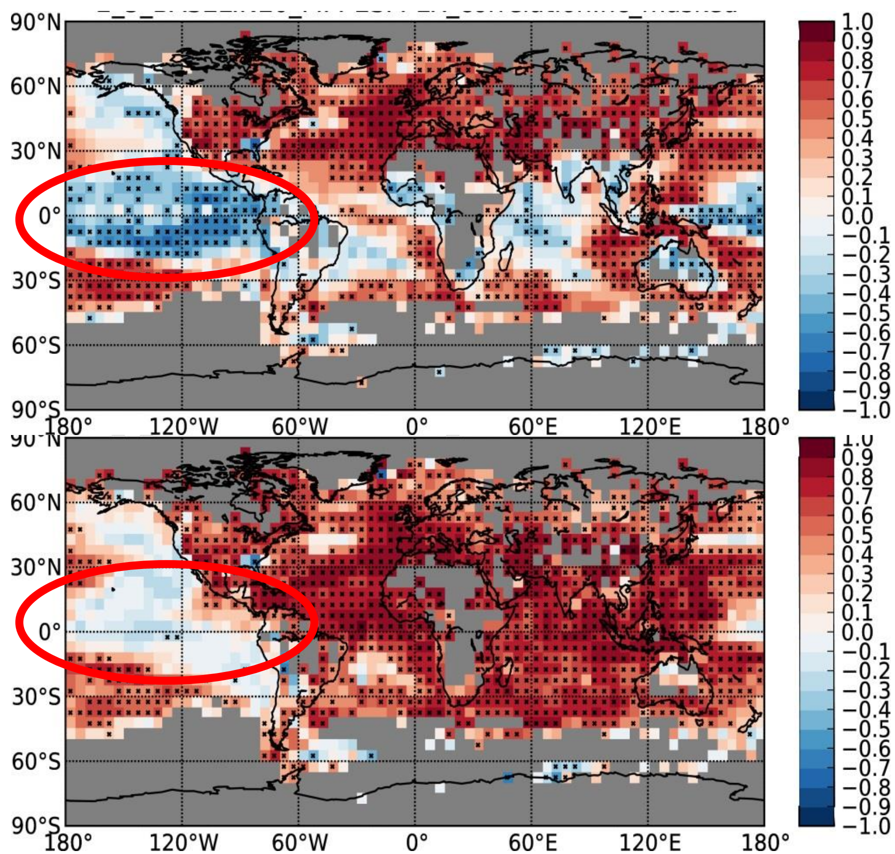
Gray et al. (2014, GRL)

Drift sources: initial conditions

Correlation of the ensemble mean 2-5 year hindcasts of surface temperature performed with the MPI-OM system over 1960-2012 using (top) CMIP5 (ocean forced with NCEP/NCAR reanalysis) and (bottom) MiKlip (nudging towards ORAS4) initial conditions. Change in the negative skill over the tropical Pacific, even using the same climate model.

CMIP5 version

MiKlip system

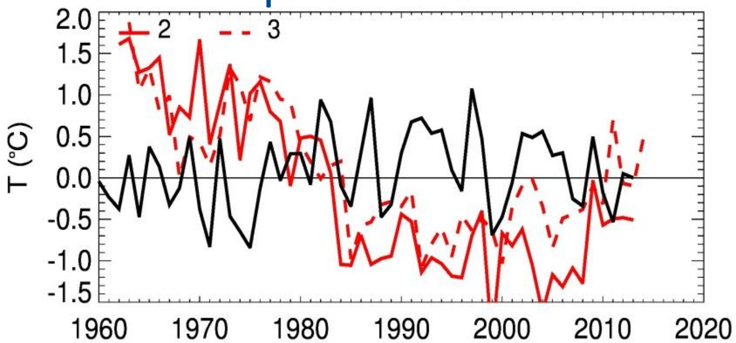


Pohlmann et al. (2013, GRL)

Drift sources: initial conditions

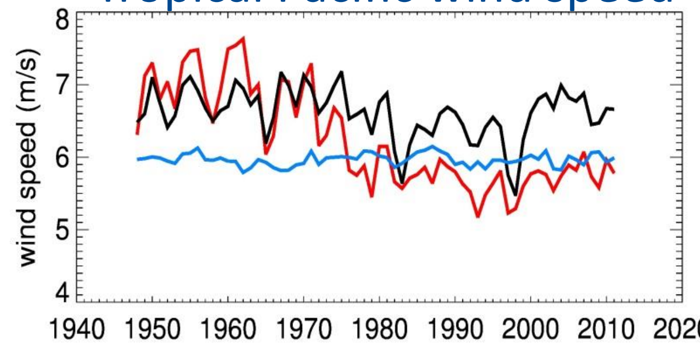
Hindcasts and analyses used in the MPI-OM system for CMIP5 (assimilation run of ocean forced with NCEP/NCAR reanalysis). Spurious trend in NCEP/NCAR winds -> trend in mixed layer depth.

Tropical Pacific SST



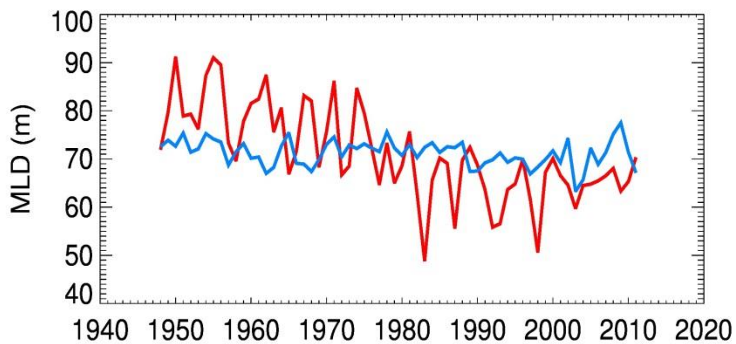
hindcasts (year 2 and 3), obs

Tropical Pacific wind speed



NCEP/NCAR, NOAA 20C, historical

Tropical Pacific MLD



assimilation (ini. state), historical

Pohlmann et al. (2013, GRL)

Drift sources: initial conditions

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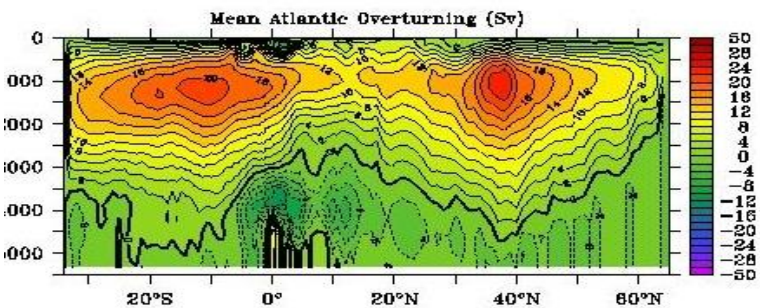
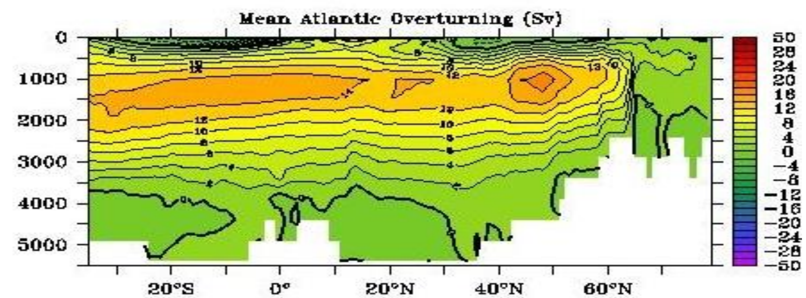
Atlantic mean meridional overturning circulation in several ocean reanalyses. Unconstrained variables may introduce large uncertainties in the initial conditions.

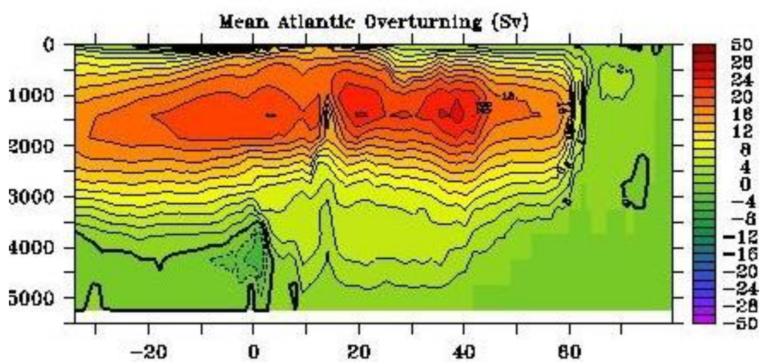
GFDL



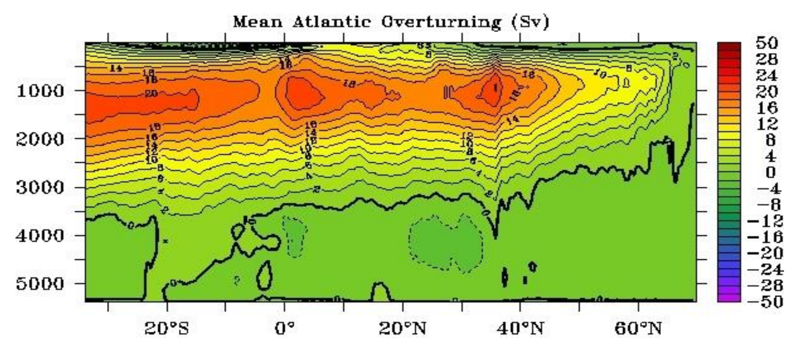
ECCO



CMCC



SODA

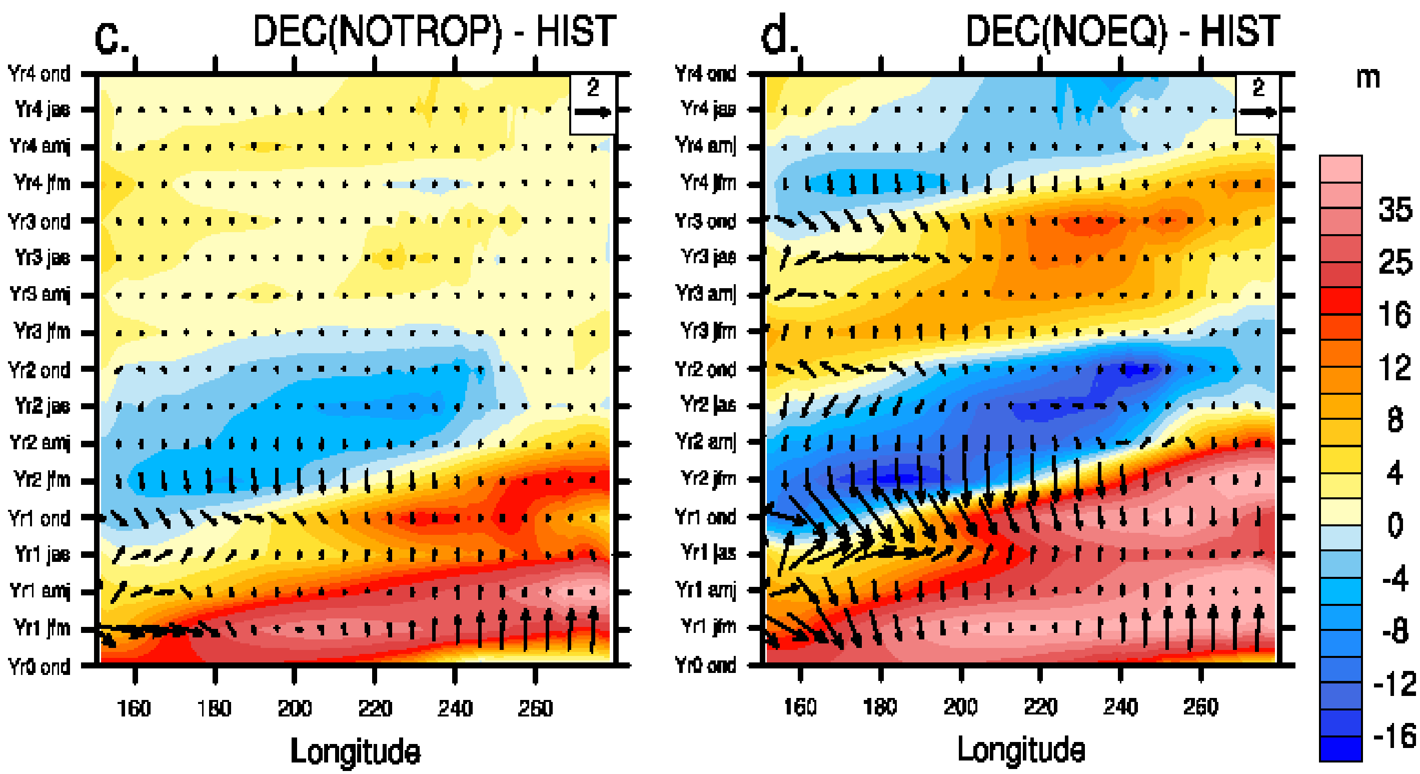


A. Koehl (Contribution to CLIVAR's GSOP)

Drift sources: initial conditions

Lead-time (from OND Year 0 to OND Year 3) versus longitude diagram for two CNRM-CM5 decadal prediction experiments where the "assimilation run" uses relaxation and nudging including (right) and excluding (left) the tropics.

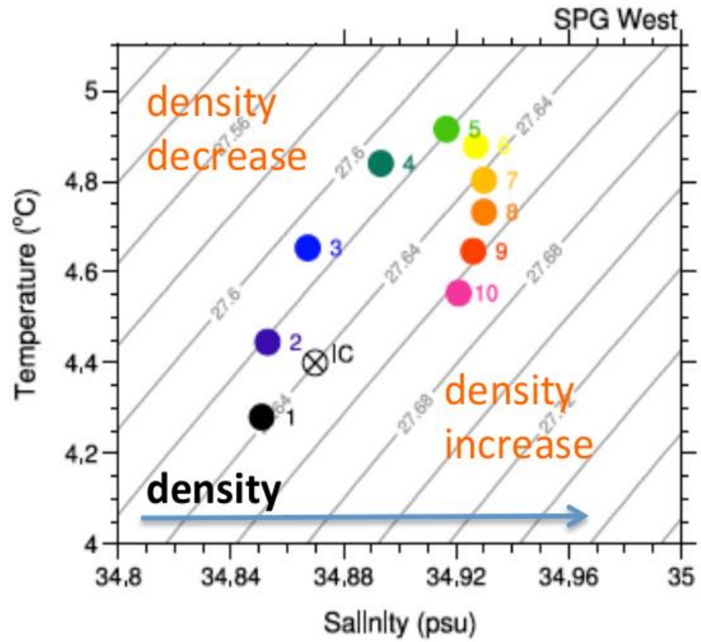
Differences of 20ºC isotherm depth (colours) and 10-meter winds (arrows) averaged over 2ºS-2ºN wrt the historical run. Start dates every 5 years over 1960-2005.



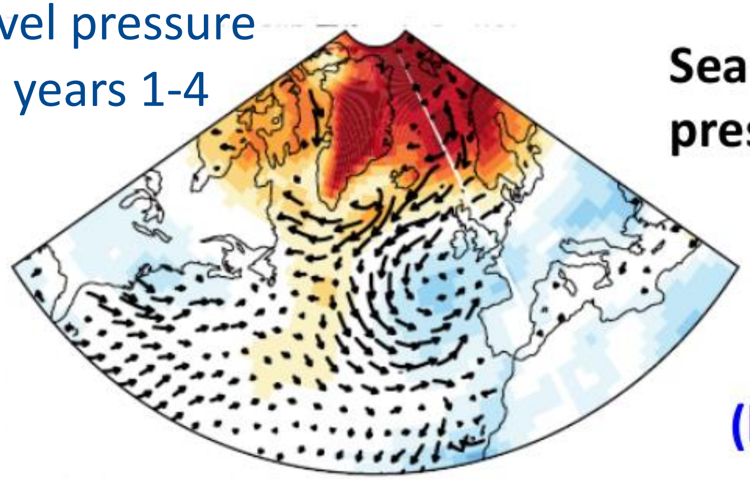
Sánchez-Gómez et al. (2014, Clim. Dyn.)

Drift uses: interacting drifts

Drift of the top 700 m in the western North Atlantic subpolar gyre in the CNRM-CM5 decadal predictions with tropical nudging in the assimilation run: initial warming, reduction of the AMOC, then cooling and desalination.

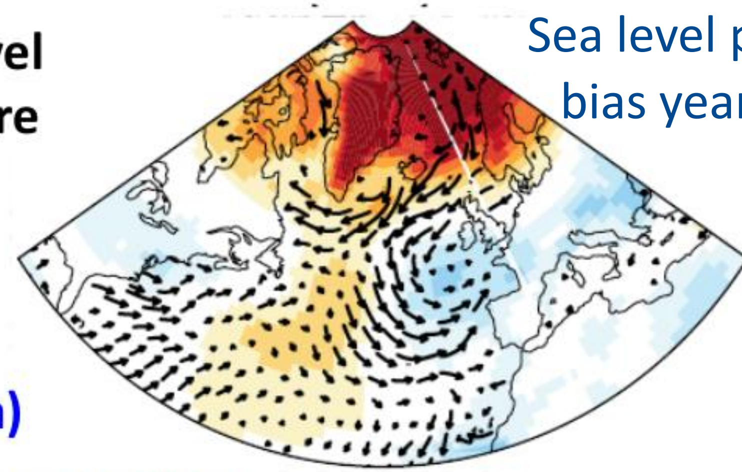


Sea level pressure bias years 1-4

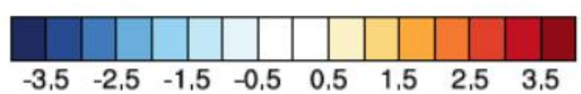


Sea level pressure

(hPa)



Sea level pressure bias years 5-10



Sánchez-Gómez et al. (2016, unpublished)

Drift uses: uncovering model errors

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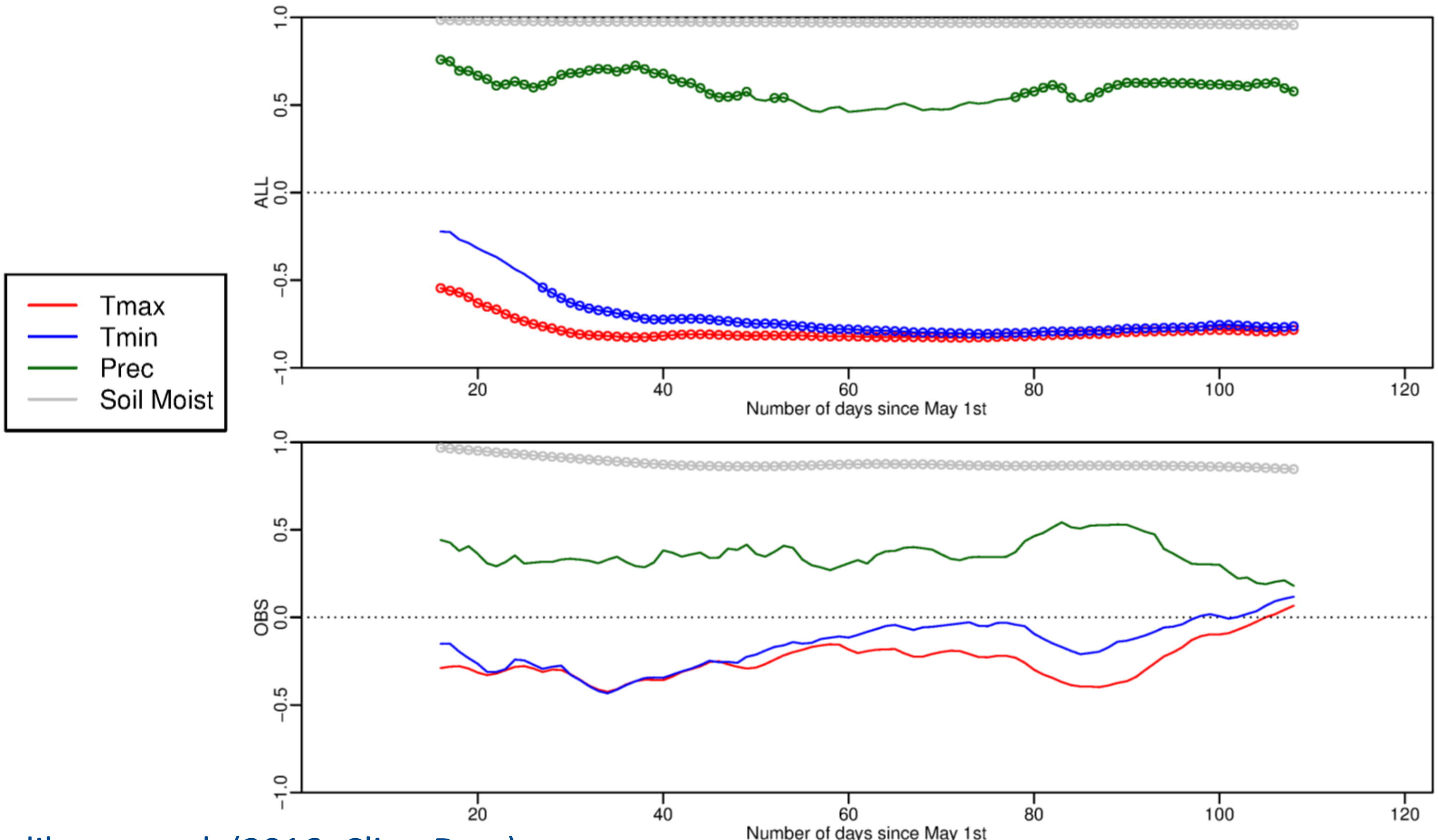
Correlation between 1st of May total soil water content and 31-day running mean of variables from the SPECS multi-model seasonal forecast (top) and ERAInt (bottom) over North American Great Plains.

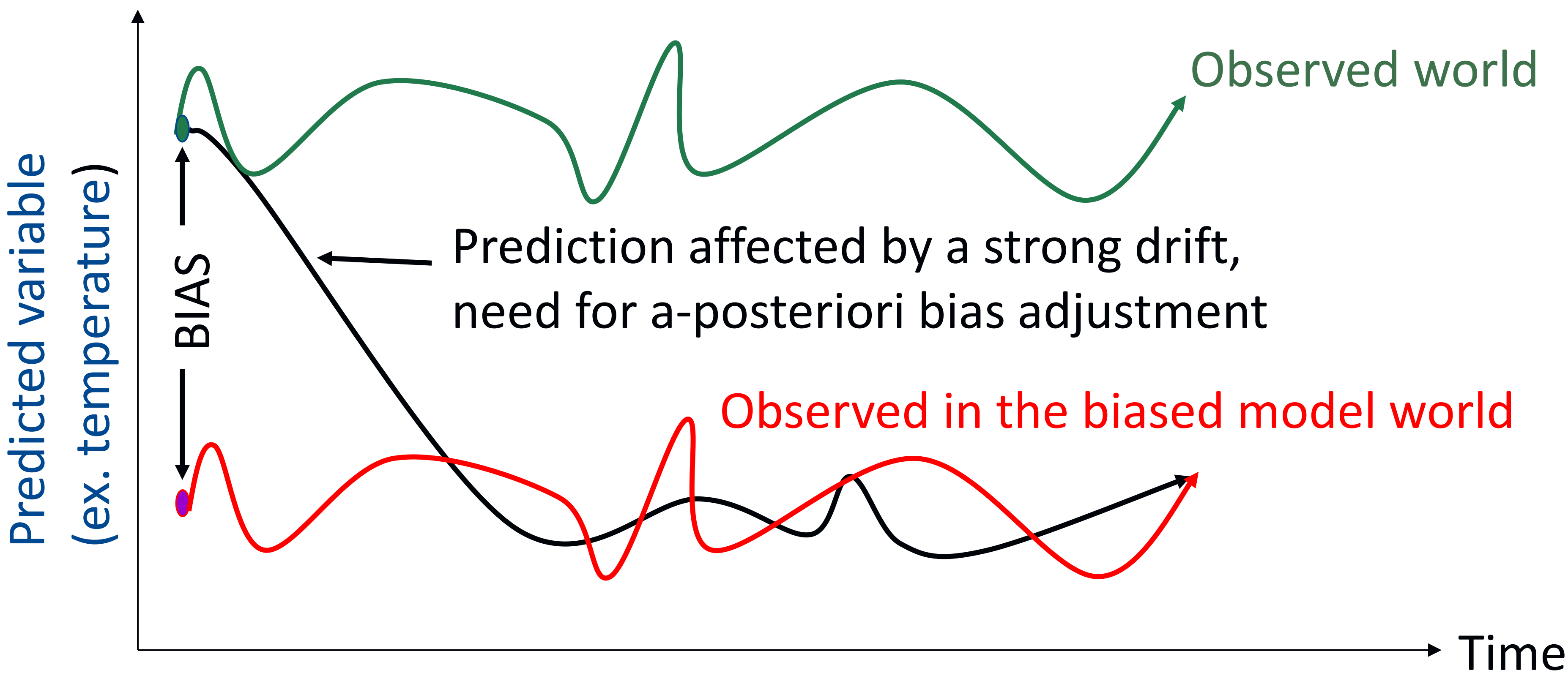
The model shifts quickly to excessive land-atmosphere coupled state.



Ardilouse et al. (2016, Clim. Dyn.)

A potential solution: anomaly initialisation

Up to now all the examples used full-field initialisation.

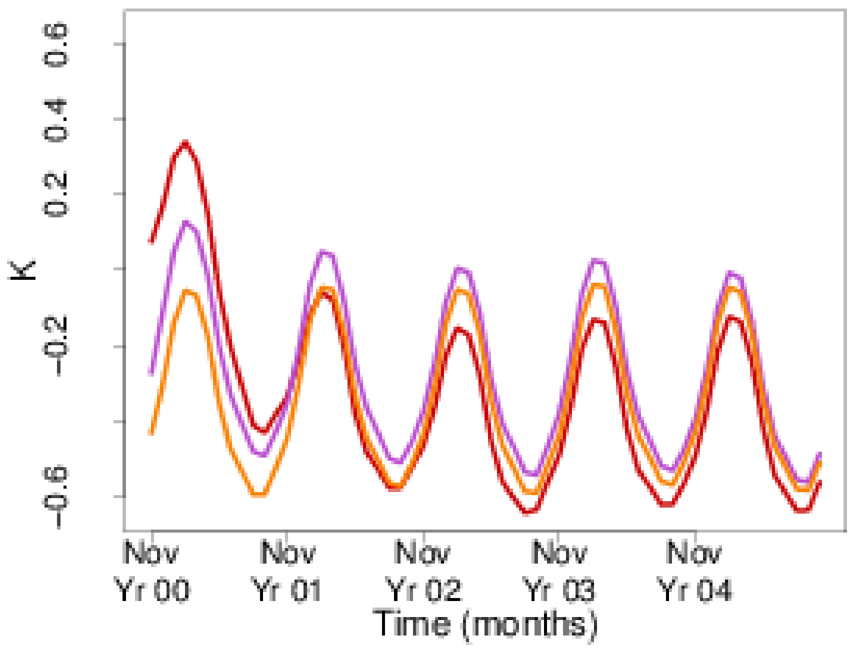


A prediction can also be formulated with anomaly initialisation: start from the observations imposed on an estimate of the model climate.

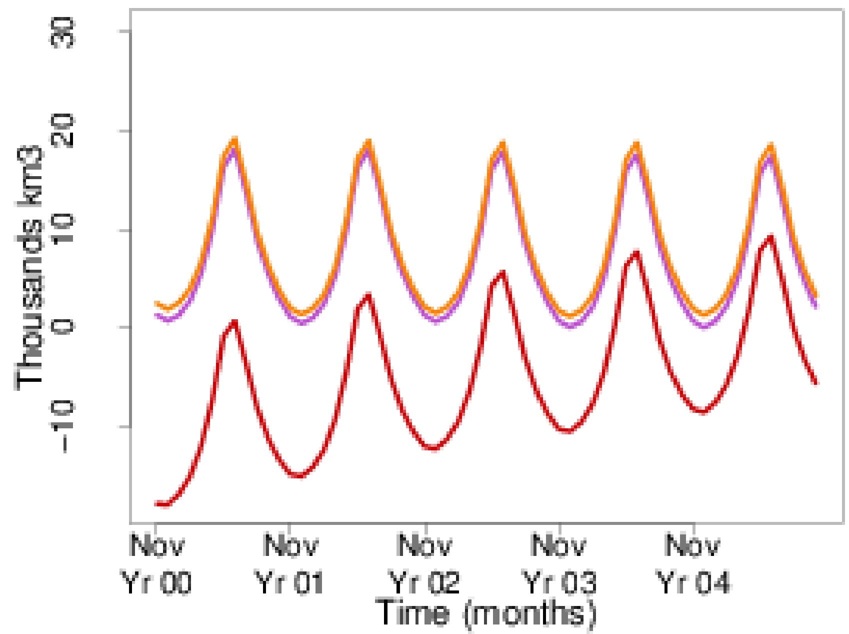
Alternatives are flux correction, anomaly coupled and super-model.

Assessment of full-field (red) and anomaly (purple, anomalies only in the ocean and sea ice) initialisation with EC-Earth2.3 to determine the influence of the drift on the forecast quality. Comparison with historical ensemble simulation (orange).

Global-mean SST



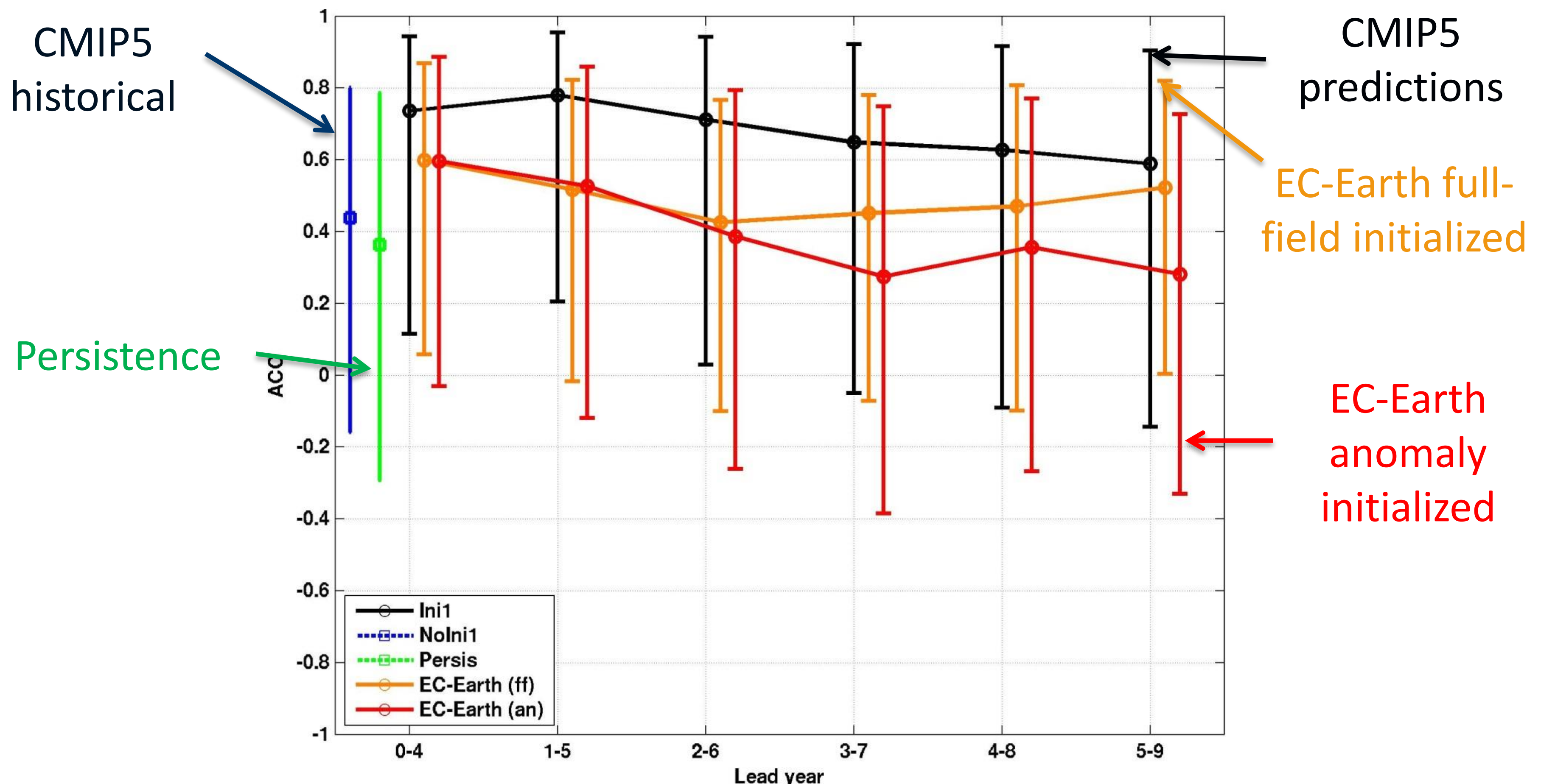
Sea-ice volume



Volpi et al. (2014, PhD thesis)

Anomaly and full-field initialisation

Correlation for the frequency of hurricanes for forecast periods of four years estimated from observations (HurDAT) and from EC-Earth CMIP5 decadal predictions. Correlation shown with 95% confidence intervals.



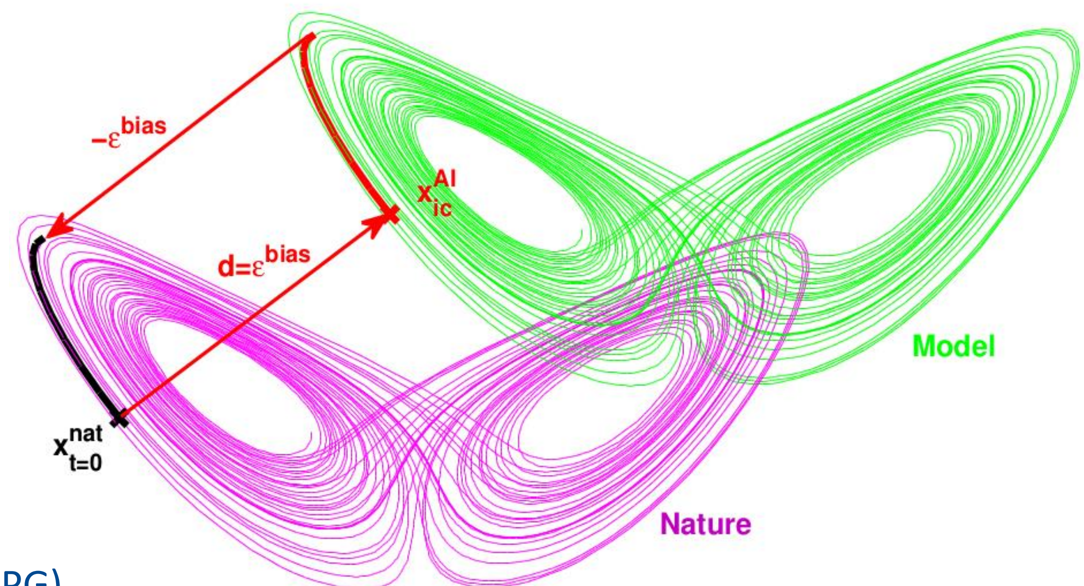
Caron et al. (2014, GRL)

Understanding AI and FFI

Full-field initialisation (FFI) starts from realistic initial conditions. It reduces the initial error but drifts and can have initial shocks.

At the expense of a larger initial error, anomaly initialisation (AI) attempts to keep initial states closer to the model attractor and to reduce drift and initial shocks.

AI can be seen as a linear mapping, where the mapping vector is a state-independent constant. The mapped state should be on the model attractor.



Carrassi et al. (2014, NPG)

Understanding AI and FFI

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360 decadal predictions were performed and compared to a nature run using the Lorenz model with three compartments, ocean, tropical atmosphere and extra-tropical atmosphere (Peña and Kalnay) for a range of values of two different parameters. The two parameters were used to discriminate between the AI and FFI performances.

Extratropical Atmosphere

$$\dot{x}_e = \sigma(y_e - x_e) - c_e(Sx_t + k_1)$$
$$\dot{y}_e = rx_e - y_e - x_e z_e + c_e(Sy_t + k_1)$$
$$\dot{z}_e = x_e y_e - bz_e$$

Tropical Atmosphere

$$\dot{x}_t = \sigma(y_t - x_t) - c(SX + k_2) - c_e(Sx_e + k_1)$$
$$\dot{y}_t = rx_t - y_t - x_t z_t + c(SY + k_2) + c_e(Sy_e + k_1)$$
$$\dot{z}_t = x_t y_t - bz_t + c_z Z$$

Ocean

$$\dot{X} = \tau\sigma(Y - X) - c(x_t + k_2)$$
$$\dot{Y} = \tau rX - \tau Y - \tau SXZ + c(y_t + k_2)$$
$$\dot{Z} = \tau SXY - \tau bZ - c_z z_t$$

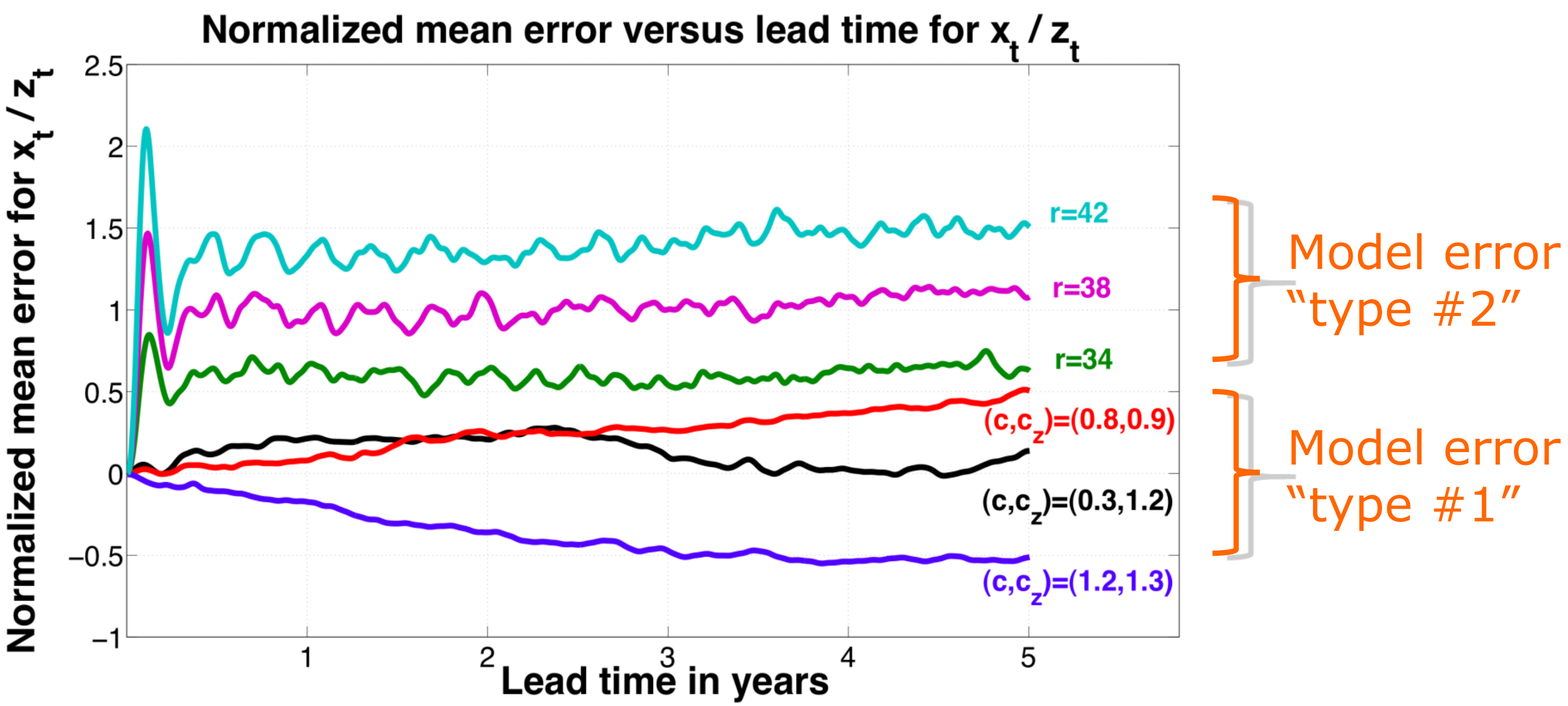
Forcing error: r

Coupling error: c, c_z

Carrassi et al. (2014, NPG)

Understanding AI and FFI

Mean error of two selected variables in FFI predictions. The configurations where AI outperforms FFI are associated with a strong initial shock and a larger bias.



Carrassi et al. (2014, NPG)

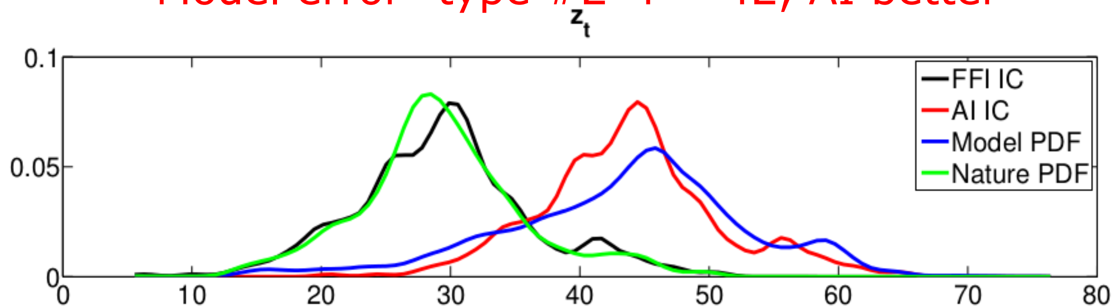
Understanding AI and FFI

PDFs of initial conditions (black/red) and of the model and “nature” climatologies (blue/green) for the Peña and Kalnay model.

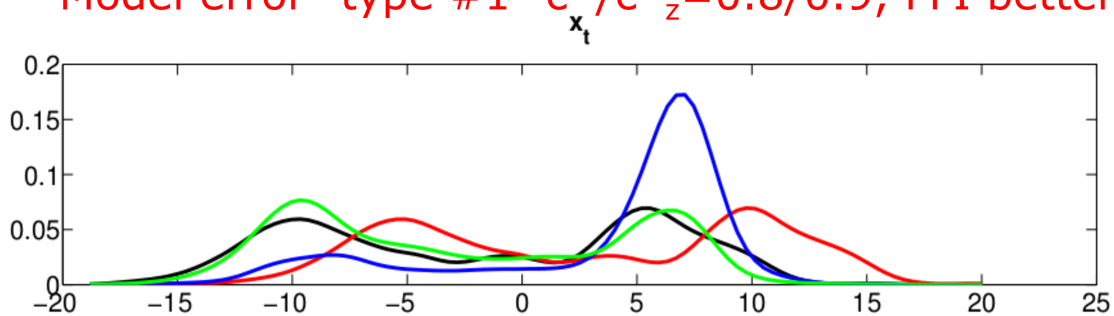
AI performs better if the differences with respect to the nature PDF are limited to the first-order moment. Differences in the higher order moments must be negligible.

Tested with other models with similar conclusions.

Model error “type #2” r^m=42, AI better



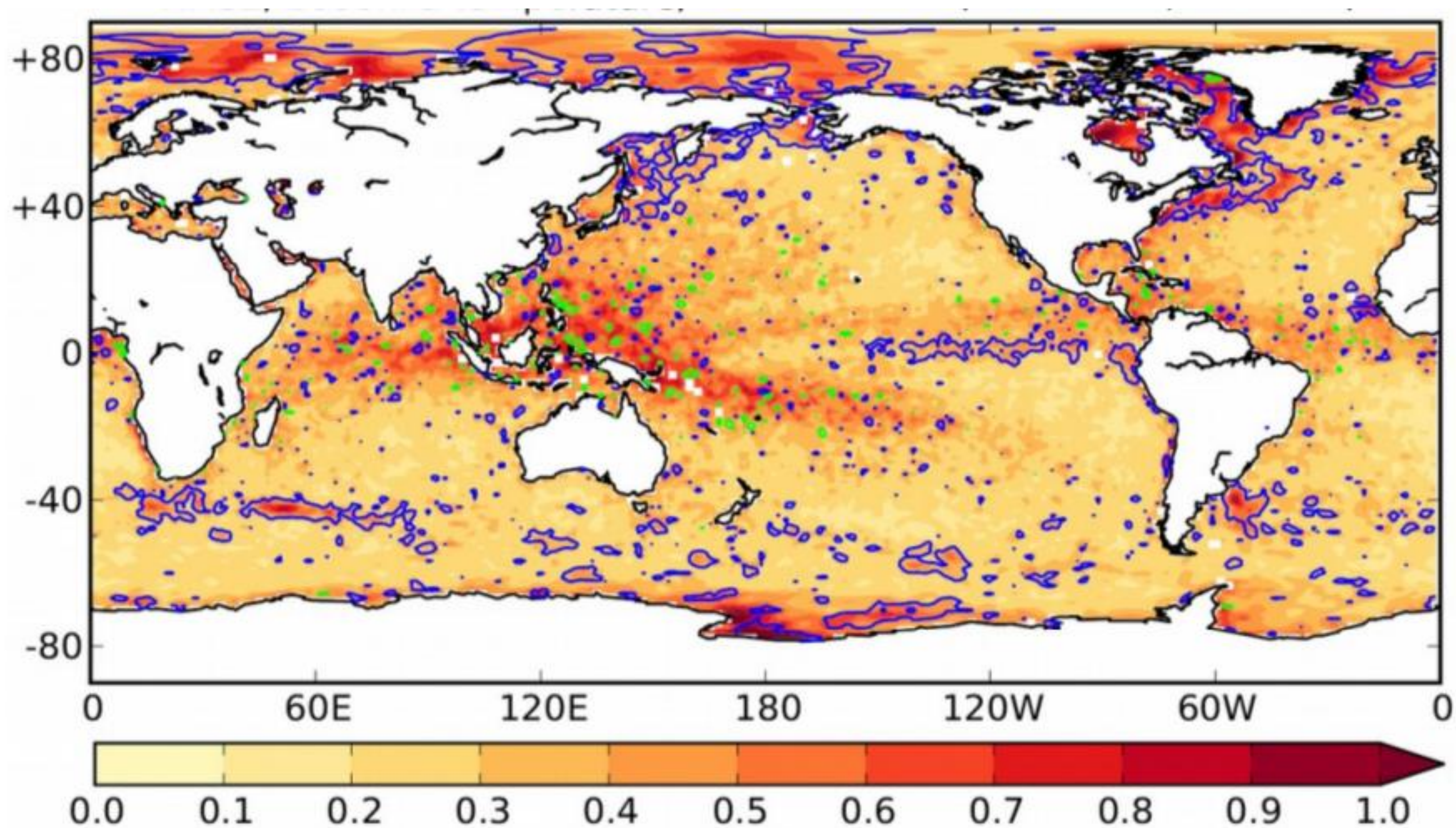
Model error “type #1” c^m/c^m_z=0.8/0.9, FFI better



Weber et al. (2015, MWR)

Balanced initialisation

1000 hPa temperature RMSE (versus its own analysis) after 12 hours in the coupled forecasts initialised from ECMWF's CERA (coupled, shades) and uncoupled (blue contours for RMSE increases) analysis.



P. Laloyaux (2016, SPECS/PREFACE/WCRP drift meeting)

Summary

- Drift, which is not necessarily monotonic, is the result of the model tending towards its own attractor. Initial shock is the result of the model rejecting a part of the initial conditions.
- Both initial conditions and model systematic error are important.
- Current drift analysis uses initialised predictions, partial coupling experiments, flux correction, anomaly coupling, etc.
- Drift can be either stationary or non-stationary (changes in observing system, trends). Busted forecasts and apparent low-frequency predictability to be analysed from a physical perspective.
- Coupled data assimilation (seamless) offers a promising way forward. A better use of analysis increments should be made.

- The idea that resides behind the relevance of the drift is the expected relationship between forecast quality and model fidelity.